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A comparative assessment of multi-criteria decision-making methods for prioritizing urban flood hazard potential based on geomorphometric parameters

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ABSTRACT

Objective: Prioritizing sub-watersheds is a key component of watershed management, particularly in regions prone to hydrological extremes. This study investigates the influence of morphometric characteristics on flood hazard assessment in the Kan watershed, located in northwest Iran.

Methodology: To achieve this, the weights of morphometric parameters were determined using three different weighting approaches, and ArcGIS 10.2 was employed to derive 17 morphometric indices for flash-flood modeling. Subsequently, multi-criteria decision-making (MCDM) models were applied to rank the sub-watersheds based on their flood-generating potential.

Findings: The Analytical Hierarchy Process (AHP) identified the Imamzadeh Davood, Talun, and Sangan sub-watersheds as the highest-priority zones with scores of 0.74, 0.50, and 0.41, respectively. Using the Analytic Network Process (ANP), the highest rankings were assigned to Imamzadeh Davood (0.97), Talun (0.51), and Doab (0.48). The Shannon Entropy method similarly ranked Imamzadeh Davood, Talun, and Rendan as the top three sub-watersheds with scores of 0.97, 0.68, and 0.52. Imamzadeh Davood and Talun consistently appeared as high-priority areas across all methods. Validation using the HEC-HMS hydrological model and statistical analyses confirmed the reliability of the MCDM techniques, with TOPSIS, ANP, and Shannon Entropy emerging as the most robust approaches.

Conclusion: Overall, the findings demonstrate that integrating morphometric analysis with MCDM frameworks provides an effective and practical tool for flood hazard prioritization and watershed management in arid and semi-arid regions.

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1. Introduction

Floods are one of the world's major natural hazards, causing considerable destruction every year, including infrastructure disasters and threats to human life and property (Mukherjee & Singh, 2020) Furthermore, the expected impacts of climate change indicate that the frequency and intensity of extreme precipitation events, as well as the probability of flash floods, are increasing (Adnan & Kreibich, 2016 ;Field et al., 2012 ;Rahman et al., 2019) . Analyzing the spatial distribution of surface runoff generation and the subsequent attenuation of floods within a watershed stream network is a prerequisite for any flood control strategy (Dehghanian et al., 2020). It is expected that more than 1.3 billion people will be affected by the hazard of floods by 2030 (Falah et al., 2019).

On the 28 of July ,2022, Severe flooding in the Imamzadeh Davood of Tehran in Kan River caused extensive damage, leaving significant traces of devastation throughout the area**.** This occurrence acts as a stark warning regarding the escalating danger of floods. The devastating impact of recent flooding underscores the urgent necessity for proactive urban flood management strategies in the region to effectively alleviate associated risks. Also, the proximity of the Kan River to Tehran and its recent designation as a recreational area have led to increased construction along its banks. Large-scale construction projects have been carried out without consideration for the river's buffer zone or previous flooding events. Consequently, it is essential to address this area by prioritizing the flood potential of the sub-basins and implementing effective flood control measures within the watershed. Identifying potential floods in sub-watersheds is crucial for minimizing the impact of natural disasters.

The physical characteristics of a watershed are among the most significant factors influencing natural hazards; meteorological, hydrological, and water and soil conservation issues are intricately connected to it.(Dovonce, 2000). Due to the challenging conditions in managing the country's watersheds, runoff has a notable capacity to generate floods and transport sediments. It is necessary to investigate the morphometry of the watershed to gain an overview of the drainage structure, which is a crucial aspect for ranking watersheds (Strahler, 1952). The parameters of morphometric analysis assist in identifying and understanding the physical characteristics of the watershed and its connection to flood occurrences (Bhatt & Ahmed, 2014). Moreover, morphometric prioritization is a significant tool for studying the processes operating in a watershed and its management (Singh et al., 2020). Therefore, efficient flood management necessitates identifying the sources of flooding in watersheds and prioritizing sub-watersheds (Amiri et al., 2019). .

Multi-Criteria Decision-Making (MCDM) methods have been widely applied in diverse water management domains, including evaluating flood management alternatives, facilitating the optimization of resource allocation, and appraising flood hazard potential (Malekian & Azarnivand, 2016 ;Roy & Blaschke, 2015 ;Yang et al., 2013 ;Guo et al., 2014). A significant number of studies have been carried out to prioritize sub-catchments utilizing MCDM models that take into account various criteria (Ahmadisharaf et al., 2015 ;Rahman et al., 2019 ;Chung EunSung et al., 2014 ; Ghadimi et al., 2024; Ghadimi. et al, 2013). For example, Aher (2014) used Fuzzy Analytical Hierarchy Process (FAHP) techniques and morphometric characterization to plan and manage sub-watersheds, demonstrating that FAHP is a viable technique for assessing soil and water hazard. Therefore, prioritizing sub-watersheds is essential for watershed management and flood control. Gopinath (2016) found that morphometric analysis, along with multi-criteria decision-making, was an efficient tool in watershed planning. The length of overland flow and drainage texture were identified as the most influential parameters in watershed conservation. Meshram (2020) showed that GIS and RS methods, in combination with MCDM approaches such as TOPSIS, SAW, Borda, and Copland, can assist in the prioritization of sub-watersheds, contributing to the control of watersheds and the protection of water resources. Gholami et al. (2020) studied the flood stage and floodplain partitioning of the Kan watershed using HEC-RAS and the HEC-geo-RAS supplement to examine flooding levels in the main branch for return periods of 2, 5, 10, and 20 years. The increase in the water level upstream was attributed to a rise in flow, leading to reduced lateral expansion in floodplains based on a hydrodynamic model. The AHP technique in ArcGIS has been used to assess flash flood susceptibility in Saudi Arabia, and the results indicate that rainfall, TWI, DEM, and slope significantly influence the flood hazard mapping of the study area of the study area. (Shakoor et al., 2024).

Rehman et al .(2024) presented vegetation condition affected peak discharge. The main role of rigid vegetation is to act as a direct barrier against the effects of rainfall. In contrast, flexible vegetation exhibits greater resistance, as surface runoff consistently encounters obstacles along its path.

However, the river's dimensional change is more pronounced in the middle and lower slopes because of the decline in water level, resulting in larger floodplains in these areas compared to the upper sections of the river. Additionally, to prioritize watersheds of the Aras River in Türkiye based on the morphometric analysis and principal component analysis methods, specifically, the linear, areal, and relief morphometric properties of the investigated watersheds, the study found a correlation between watersheds with high-priority flood potential and actual flood occurrences (Ghasemlounia & Utlu, 2021). Indeed, Obeidat et al., (2021) conducted a study to prioritize watersheds for flood hazard management in Jordan, utilizing geospatial technology to assess morphometrics. According to the prioritization results, approximately 71% of sub-watersheds are highly susceptible to floods. The study revealed that combining morphometric analysis with GIS could be a valuable tool for understanding sub-watersheds in relation to flood control. Teimouri et al. (2022) utilized TOPSIS, SAW, ELECTRE, and VIKOR models to prioritize flood hazards in a watershed. The TOPSIS and VIKOR methods, showing the lowest percentage of change, were ranked first, while the ELECTRE method exhibited the highest percentage change.

Ghadimi et al.(2022) ranked the flood potential of Kan sub-watershed based on morphometric parameters and revealed that climate and morpho-topography were significant factors affecting flooding in the AHP method, while slope, concentration time, and rainfall intensity were crucial in the ANP method. The Multi-Criteria Decision-Making (MCDM) methods, such as the Analytical Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), are employed in India to prioritize regions prone to erosion .The adopted methods consider morphometric parameters for soil conservation, with the AHP approach proving to be more predictive than other models (Kumar & Sarkar, 2022) .Mahammad et al. (2022) used morphometric characteristics to assess the flood potential of the Gumani River watershed in India and prioritized it using the TOPSIS approach. They calculated linear, areal, and relief aspects and discovered that relief features are the most important, followed by areal and linear aspects.

In recent years , methods such as MADM for assigning weights to parameters have gained considerable attention because of their capacity to reduce subjective judgment in the decision-making process (Mahmoodi et al., 2023). The Kan watershed, located in Iran, was selected as the study area, and 17 morphometric parameters were chosen for analysis. The parameter weighting methods reduce the subjective bias in the decision-making process; for this reason, the approach has attracted considerable attention. MCDM is a powerful tool for flood management and watershed prioritization concerning the flood potential of the sub-watershed However, no research has been carried out to analyze the effect of morphometric parameters and weighting methods in identifying and prioritizing flood potential of sub-watersheds. The main purpose of the current study is to compare six weighting approaches, including ANP[1],AHP[2],TOPSIS[3],COPRAS[4],VIKOR[5], and Shannon Entropy, for watershed prioritization based on flood generation and to gain accurate knowledge of morphometric variables affecting the Kan watershed. This study aims to: (1) analyzing morphometric parameters that affect flood generation using GIS, (2) ranking the critical sub-watersheds using the six weighted methods of the MCDM model (3) validating the outputs of the MCDM approaches through the Spearman Correlation Coefficient Test (SCCT) and Kendall Tau Correlation Coefficient Test (KTCCT) (4) choosing the best method for ranking of sub-watersheds (Fig 1).

Notation

A Area of watershed (km²)
P Perimeter of watershed (km)
Lu Total stream length of all orders (km)
Lb Basin length (km)
Dd Drainage density (km/km²)
Fs Stream frequency (number/km²)
Rb Bifurcation ratio (dimensionless)
Lg Length of overland flow (km)
Rn Ruggedness number (dimensionless)
Re Elongation ratio (dimensionless)

1. Analytical Network Process
2. Analytical Hierarchy process
3. Technique for Order Preference by Similarity to Ideal Solution
4. Complex Proportional Assessment
5. Vlse Kriterijumsk Optimizacija Kompromisno Resenje

Rc Circularity ratio (dimensionless)
Ig Infiltration number (dimensionless)
Tc Time of concentration (hours)
n Normalized value of the criterion
x_ij Value of criterion j for sub-watershed i
min (xj) Minimum value of criterion j among sub-watersheds
max (xj) Maximum value of criterion j among sub-watersheds
AHP Analytical Hierarchy Process
ANP Analytical Network Process
TOPSIS Technique for Order Preference by Similarity to Ideal Solution
COPRAS Complex Proportional Assessment
VIKOR Vlse Kriterijumska Optimizacija Kompromisno Resenje

2. Study area

The Kan watershed is situated in the northwest of the capital city, Tehran, and boasts the longest stream among the northern watersheds. The Kan watershed is divided into 10 minor sub-watersheds known as Imam-Zadeh Davood, Talun, Rendan, Kiga, Sangan, Keshar, Sulqan, Middle Kan, Doab, and Harias. It extends from 51° 10′ 2″ to 51° 22′ 35″ E longitude and from 35° 46′ 23″ to 35° 57′ 14″ N latitude, covering an area of 220.571 km². The Kan watershed is the most significant stream, originating from the heights above Imam Zadeh Davood and continuing to exit the watershed in the residential areas of Kan. Other important watershed channels include Lalon, Talun, and Keshar. The temperature of the region ranges from 7.3°C to 43°C, with an average annual precipitation of 625 mm, concentrated between March and July. The Kan watershed, with an average slope of 52 percent, has a Mediterranean precipitation regime, where the majority of flood events occur during the spring and early summer. The flow rate of the discharge varies from 0.29 m³/s to 7.64 m³/s, with a maximum flash flood discharge of 10.2 m³/s. In recent years, due to the increased population in the Kan watershed as a recreational area, construction activities along the river have been accelerated. Implementation of large projects without considering riverbank protection, coupled with a relative increase in housing density and population growth due to high rates of migration, along with land use changes, highlights the special importance of studying this area in terms of flash floods.

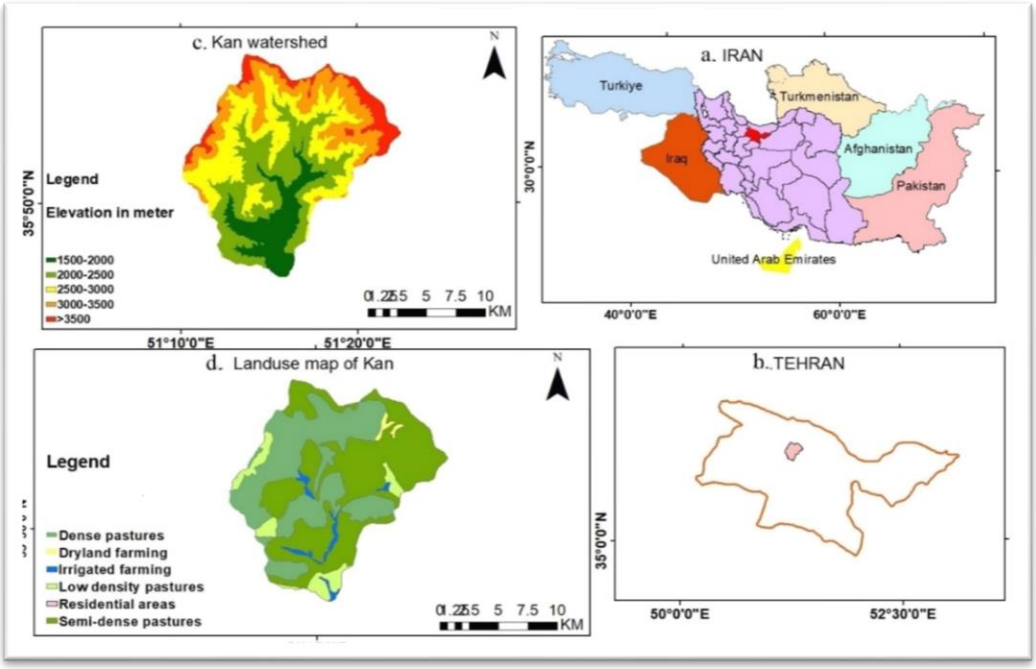

Fig. 1. a: Location map of the study area in Iran, b: Location of the Kan watershed in Tehran province c: The elevation map of the Kan watershed, d: The land use map of the Kan watershed

3. Materials and methods

In the present research, the digital elevation model (DEM) of the watershed was obtained from topographic maps with a 10-meter resolution. Sub-watersheds were delineated, and the stream network was extracted using the Strahler method in the ArcGIS 10.8.2 using Arc hydro tool. The first step in hydrologic modeling involves filling the elevation grid. Flow direction is a critical aspect of hydrological modeling, as it aids in identifying the drainage patterns within a landscape. This process entails establishing the flow direction for every cell in the landscape, which is accomplished by calculating it for each pixel using the filled Digital Elevation Model (DEM) (Fairfield & Leymarie, 1991) . In the next step, the flow accumulation grid is obtained, and the stream network is outlined according to the length of each stream, which is determined by the threshold value for flow accumulation. Extraction of the drainage network involved considering pixels with a threshold of 100 (Azizian & Shokoohi, 2015).

The parameters that significantly influenced the priority and flood scenario in the study area were identified, and their values were subsequently calculated. In many prior studies, the results obtained through morphometric analysis are often generalized without identifying hazard hotspots. The outcomes of such studies have limited utility in flood hazard mitigation. For this reason, the current study seeks to comprehend the relative flood hazard situation of the watersheds by calculating the values of the chosen morphometric parameters using various mathematical methods. Furthermore, morphometric parameters for each sub-watershed were then determined using standard methods and formulas (Table 1). These morphometric parameters are divided into five categories: shape, linear, relief, areal, and watershed parameters. After calculating the morphometric parameters, the data were standardized. Normalization involves equalization for each parameter. For parameters with an inverse relationship with flood potential, the lowest value among the watersheds is divided by the other watershed values Eq. (1) For parameters with a direct relationship with flood potential, the values of each parameter are divided by the largest value among the watersheds Eq. (2). The Super Decisions, an Expert Choice software, was used to weigh the parameters for analysis. Following the evaluation of the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Shannon Entropy, flooding sub-watersheds were prioritized using the TOPSIS, VIKOR, and COPRAS methodologies (Fig 2). The target population for filling out the questionnaires was 15 individuals in the AHP and ANP approaches (Table 2) provides a summary of the methods adopted in this research. Finally, the Spearman correlation coefficient test (SCCT) and Kendall tau correlation coefficient test (KTCCT), which are bivariate correlation tests, were performed to validate the outputs of the Multi-Criteria Decision-Making (MCDM). Multi-Criteria Decision Analysis (MCDA) was selected for this study due to its ability to integrate diverse morphological and hydrological parameters into a single decision-making framework. Specifically, methods such as TOPSIS were employed because they offer a robust mechanism for ranking sub-basins based on their proximity to ideal flood-risk scenarios. Unlike more complex stochastic models, these MCDA techniques provide a practical balance between computational efficiency and the ability to handle the multi-dimensional nature of flood vulnerability. Although the MCDA method is efficient, it has certain limitations include: 1) Some of these methods require complex and time-consuming computations; 2) Dependency on input data: The accuracy and reliability of input data can significantly impact the results of these methods; 3) Sensitivity to changes: These methods may exhibit high sensitivity to changes in the weighting of criteria or the prioritization order; 4) Conceptual limitations: Some of these methods may face conceptual limitations that could have a negative impact on their performance;. 5)Lack of flexibility in incorporating qualitative criteria. Regarding data reliability, it is important to acknowledge certain limitations encountered during this study. The accuracy of the results is inherently tied to the quality of the input spatial and hydrological data. In the case of the Kan watershed, some historical rainfall data were interpolated due to the lack of dense weather stations and certain land-use maps had limited resolution. While these factors introduce a degree of uncertainty, the adopted MCDA approach was used to mitigate these inconsistencies through expert weighting.The normalization of morphometric parameters was performed using the following equations. For criteria inversely related to flood potential:

$$n_{ij} = \min(x_j) / x_{ij} \quad \text{Normalization of negative criteria} \quad (1)$$

$$n_{ij} = x_{ij} / \max(x_j) \quad \text{Normalization of positive criteria} \quad (2)$$

n: The normalized rate of the criteria, x_i :The quantity of each indicator in the desired watershed minx_i : Minimum index value between watershed, maxx_i : Maximum index value between watersheds

Table 1. **Formulas for computation of morphometric parameters of watershed**

	No	Morphometric parameters	Formula	Description	References
A. Areal aspect	1	Drainage density (Dd)	$D_d = \sum L_u / A$	L_u= total stream length of all orders, A = area of the watershed	(Horton, 1932)
	2	Infiltration factor (Ig)	$If = F_S \times D_d$	Dd = drainage density, Fs = stream frequency	(Faniran, 1968)
B. Relief aspects	3	Ruggedness number (Rn)	$R_n = \Delta H \times D_d$	Dd = drainage density H = Total relief of the watershed	(Melton, 1957) (Moore et al., 1991)
C. Shape aspects	4	Elongation ratio (Re)	$R_e = 1.128(\sqrt{A}.\, Lb)$	Lb = watershed length A = area	(Schumm, 1956)
	5	Equivalent Rectangle	$I = \frac{C\sqrt{A}}{1.12}\left[1 - \sqrt{1 - \left(\frac{1.12}{C}\right)^2}\right]$ $L = \frac{C\sqrt{A}}{1.12}\left[1 + \sqrt{1 - \left(\frac{1.12}{C}\right)^2}\right]$	I rectangle width L rectangle length	(Alizadeh, 2010)
	6	Circularity ratio (Rc)	$R_c = 12.56 \times \left(\frac{A}{P^2}\right)$	A = area P = perimeter	(Miller, 1953)
D. Linear aspects	7	Bifurcation ratio (Rb)	$R_b = \frac{N_u}{N_u + 1}$	Nu = total number of stream segments of order 'u,' Nu + 1 = number of parts of the next higher order	(Horton, 1945)
	8	Length of overland flow (Lg)	$Lg = \frac{1}{D \times 2}$	Dd = drainage density	(Horton, 1932)
	9	Stream length (Lu)	Length of the stream		(Horton, 1945)
E. Basin aspects	10	Time of concentration	$T_c = 0.949\left(\frac{L^3}{H}\right) 0.385$	H Height dispute between the highest and lowest point of the watershed, L The length of the main waterway	(Kirpich, 1940)

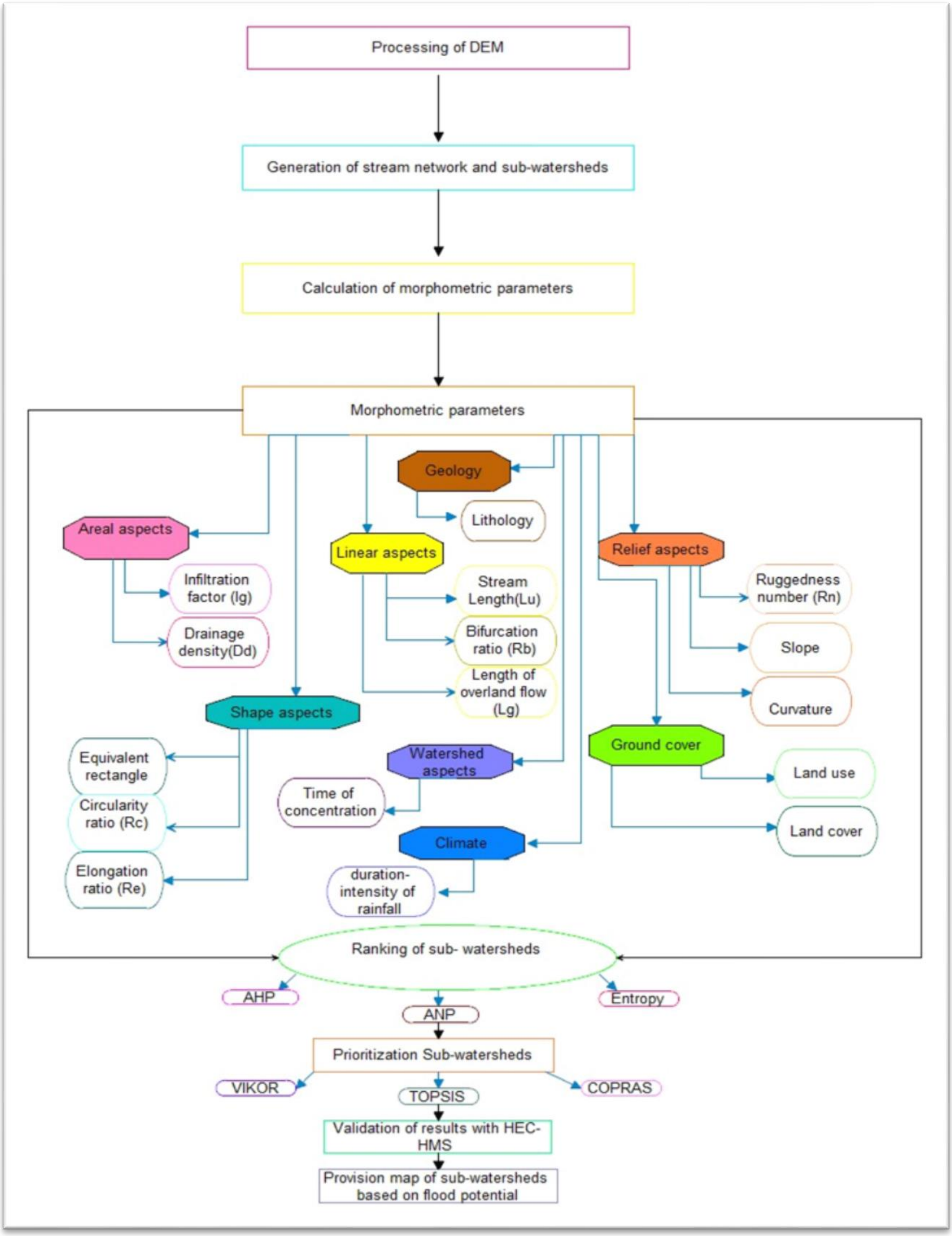

Fig. 2. The methodological procedure of the study

Table 2. Applied methods and steps in this study

Name of research method	The steps of methods	Reference
AHP	1. Hierarchical tree 2. Formation of a matrix of pairwise comparisons 3.Determine the weight and calculate the inconsistency ratio	(Saaty, 1986)
2. ANP	1. Model building and model structuring 2. Pair comparisons of priority vectors 3. Formation of Super matrix 4. Choose the best option	(Saaty, 2005)
Shannon Entropy method	1.Form a decision matrix. 2.Normalize the decision matrix. 3.Calculate the entropy of each index using the formula: $E_j = -k \sum_{i=1}^{m} P_{ij} \times \text{Ln } P_{ij}$ i=1, 2,…, m $d_j = 1 - E_j$ 5. Calculate the weights $W_j = \frac{d_j}{\sum d_j}$	(Shannon, 1948)
COPRAS method	1. Decision matrix formation technique. 2. Immeasurable decision matrix 3.Normalization using the linear method $\bar{n}_{ij} = \frac{x_{ij}}{\sum x_{ij}}$ 4. Normal rhythmic matrix $W_j \times N$ 5. Select the optimal option. $S_j^{+} = \sum d_{ij}^{+}$ $S_j^{-} = \sum d_{ij}^{-}$ 6. Calculate the utility rate $Q_i = sj^{+} + \frac{\sum_j^n = 1 \ \ sj^{-}}{sj^{-} \ \ ^{*} \ \ \sum_j^n = 1 \ \ \frac{1}{sj^{-}}}$ $u_i = \frac{Q_i}{Q_{max}} \times 100$	(Zavadskas et al., 1994)
TOPSIS method	1. Form a decision matrix 2. Compute the normalized decision matrix as follows: $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_i^m = 1 x_{ij}{}^2}}$ 3. Compute the weighted normalized decision matrix: $Vij = r_{ij} \times w_j$ 4. Determining the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) 5. Estimating the ideal and non-ideal solution i=1,2,…. . m ، $d_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+}\right)^2}$ i=1,2,…. . m ، $d_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij-v_j^{-}}\right)^2}$ 6. Determine the coefficients of the proximity of an option to the ideal solution: $cl_i^{+} = \frac{d_i^{-}}{\left(d_i^{+} - d_i^{-}\right)}$	(Hwang et al., 1981)
VIKOR method	1. Formation of the decision matrix. 2. Normalization or scaling. $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_i^m = 1 x_{ij}{}^2}}$ 3. Determining the best value (f^{+}) and worst value (f^{-}) f^{+} = Max f_{ij} f^{-} = Min f_{ij} 4. computing maximum group utility index (Si) and minimum individual regret index of opponent group values (Ri) $Si = \sum_{i=1}^{n} w_i \times \frac{f_i^{*} - f_{ij}}{f_j^{*} - f_i^{-}}$ / $Ri = \max\left[w_i \times \frac{f_i^{*} - f_{ij}}{f_j^{*} - f_i^{-}}\right]$ 5. Calculation of Vikor index $Q_i = v\left[\frac{s_i - s^{*}}{s^{-} - s^{*}}\right] + (1 - v)\left[\frac{R_i - R^{*}}{R^{-} - R^{*}}\right]$ $S^{-} = MaxS_i$ $R^{-} = MaxR_i$ $S^{*} = MinS_i$ $R^{*} = MinR_i$ 6. compute Q_i ,Si , Ri sorting them in decreasing order if the following two conditions are satisfied: C 1 “Acceptable advantage” $Q\ (A_2) - Q\ (A_1) \geq \frac{1}{n-1}$ $Q\ (A_2) - Q\ (A_1) < \frac{1}{n-1}$ 7.Ranking alternatives	(Opricovic & Tzeng, 2004)

4. Results and discussion

4.1. Weights of morphometric parameters in AHP, ANP and Shannon Entropy

The AHP, ANP and Shannon Entropy techniques are utilized to determine the weights of morphometric parameters, as illustrated in (Fig 3). In the AHP method, parameters such as slope (0.43), bifurcation ratio (0.83), circularity ratio (0.58), infiltration factor (0.73), land cover (0.83), and duration-intensity of rainfall are identified as critical elements in flooding. In the ANP method, slope, time of concentration(0.12) and climate (duration-intensity rainfall) (0.21) were among the most critical elements in flooding. Meanwhile, in the Shannon Entropy method, factors like stream length (0.15), elevation (0.11), and geology (0.11) are deemed essential for flooding. Additionally, a normalized morphometric parameter map is created for each sub-watershed (Fig 4).

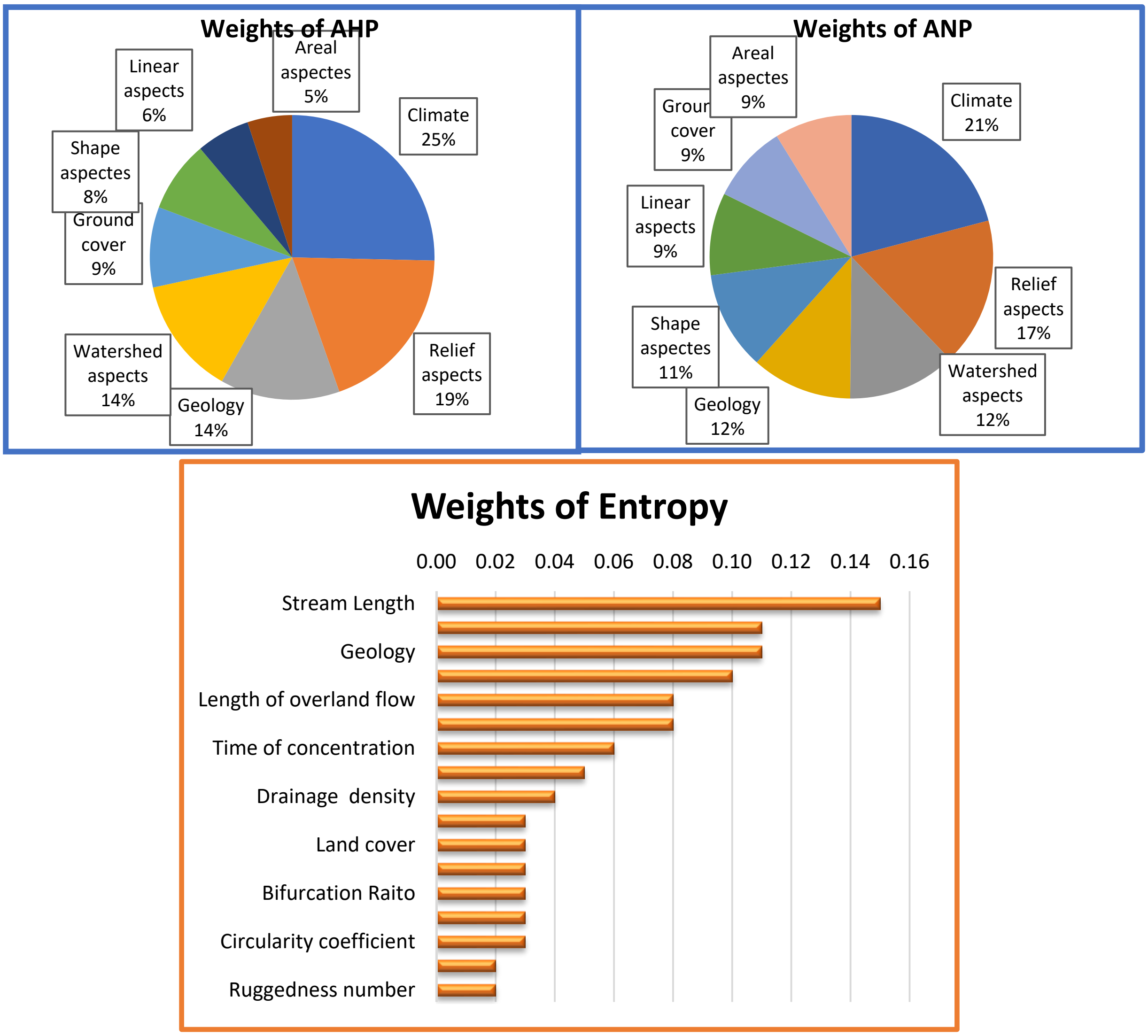

Fig. 3. Weights of morphometric parameters in AHP, ANP, and Shannon Entropy methods.

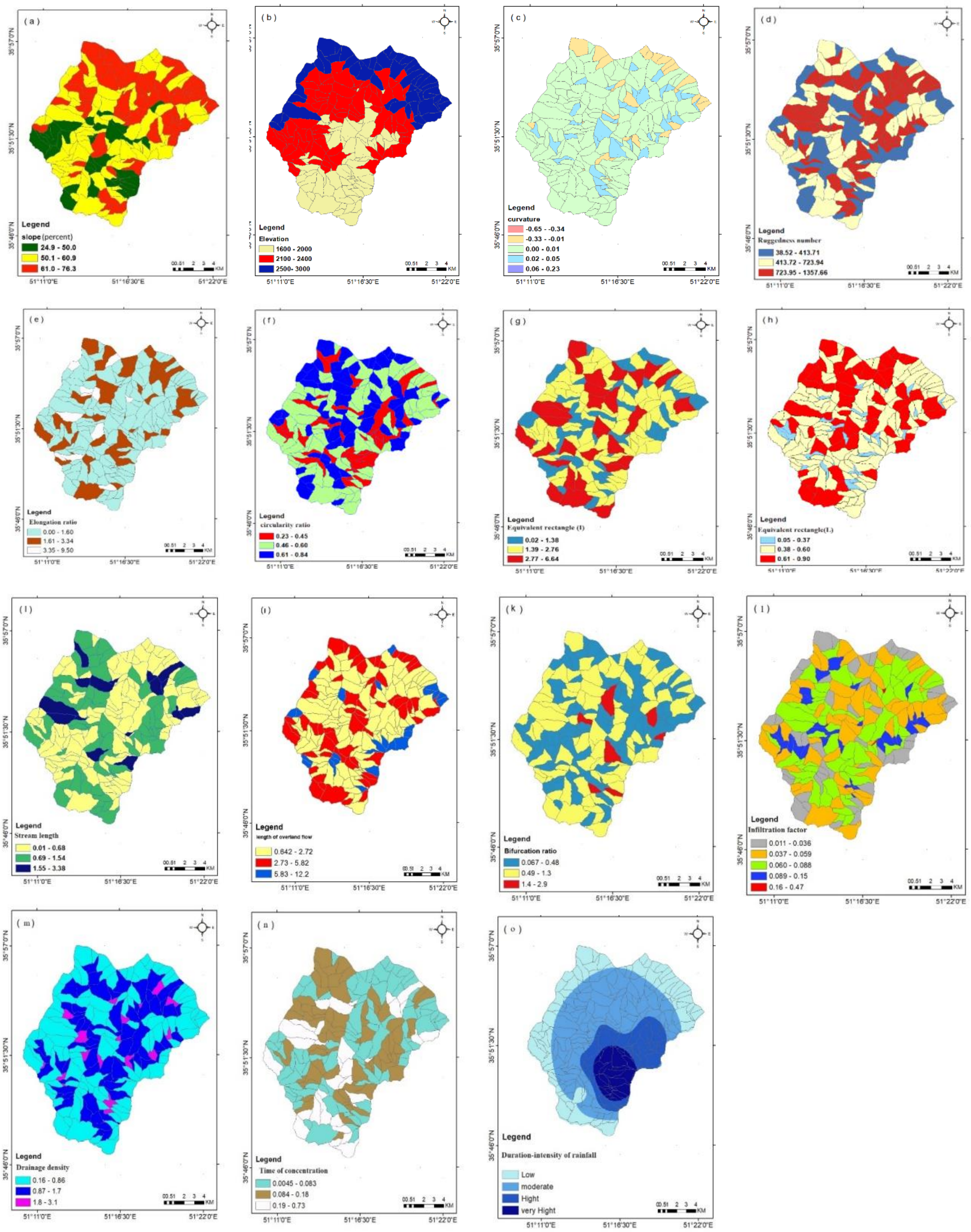

Fig 4 . Map of normalized morphometric parameters for sub-watersheds Kan: (a) slope(percent), (b) elevation, (c) curvature, (d) ruggedness number, (e) elongation ratio, (f) circularity ratio, (g) and (h) equivalent rectangle, (I) stream length, (j) length of overland flow, (k) bifurcation ratio, (l) infiltration factor, (m) drainage density, (n) time of concentration, and (o) duration-intensity of rainfall.

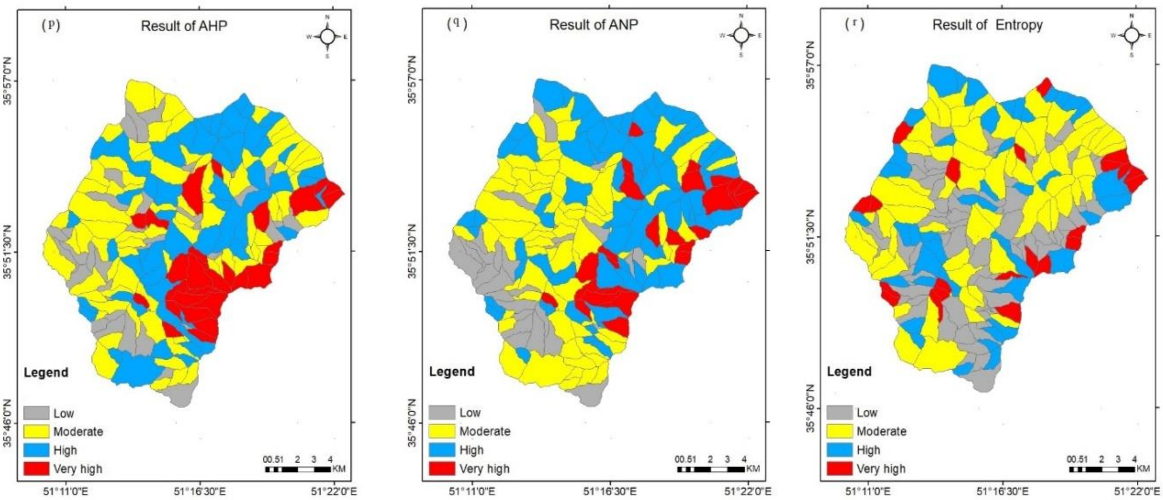

Fig. 5. The output of morphometric parameters by AHP(p) and ANP(q), Shannon Entropy (r)

4.2. Prioritization of sub-watersheds using TOPSIS, COPRAS and VIKOR

In order to prioritize the watershed, various methods such as TOPSIS, VIKOR and COPRAS were used. Also, in this study, flooding map of the watershed is generated using the normalized morphometric parameters. The hazard of flooding in sub-watersheds is then classified as low, moderate, high, or very high (Fig 5). The TOPSIS method calculated the distance between each choice (sub-watershed) using positive and negative ideals, and the sub-watersheds were ranked accordingly. In the AHP technique, the findings revealed that Imam-Zadeh Davood, Talun, and Sangan sub-watersheds scored the highest (0.74, 0.50, and 0.41), while in the ANP method, the top three were Imam-Zadeh Davood, Talun, and Doab, with the highest scores (0.97, 0.51, and 0.48). These sub-watersheds, particularly Imam-Zadeh Davood, Talun, and Rendan, ranked first through third in the Shannon Entropy technique, scoring 0.98, 0.69, and 0.53 points, respectively. Notably, there were differences in the rankings of Doab, Sangan, Rendan, Middle Kan, and Keshar sub-watersheds among these three techniques.

The COPRAS ranking method, when compared to the AHP method, indicated that Imam-Zadeh Davood, Talun, and Sulqan sub-watersheds had the highest scores (100, 95.90, and 95.87). However, in the ANP method, Talun, Imam-Zadeh Davood, and Doab sub-watersheds scored the highest (100, 99.72, and 97.69). Imam-Zadeh Davood, Talun, and Doab also showed the highest flood potential in the Shannon Entropy method, with scores of 0.61, 0.57, and 0.55, respectively. Notably, there were variations in rankings, especially for Doab, Middle Kan, Harias, Keshar, and Rendan sub-watersheds among these three techniques.

In the VIKOR technique, the top selections differed based on the methodology used. According to the ANP technique, Sangan and Talun sub-watersheds (0.09,0.17) were ranked first, while in the AHP methodology, Doab, Talun and Sangan, and took the lead (0.10,0.14 and 0.21) (Table 3). The Shannon Entropy method indicated that Talun, Imam-Zadeh Davood, and Sangan sub-watersheds (0.01,0.26 and 0.27) had higher flood intensity than others. Across all three techniques, Imam-Zadeh Davood and Talun consistently appeared as sub-watersheds with a higher hazard of flooding. These sub-watersheds are identified as the most vulnerable to flooding due to their values directly related to flood hazard. In Table 3, the TOPSIS, VIKOR, and COPRAS techniques utilized AHP, ANP, and Shannon Entropy weights to prioritize the main sub-watersheds.

Table 3. Ranking of sub-watersheds based on TOPSIS, COPRAS, and VIKOR methods

	TOPSIS						COPRAS						VIKOR					
Sub-watersheds	cl_i^+	Rank in the method AHP	cl_i^+	Rank in the method ANP	WJ	Rank in the method Shannon Entropy	u_i	Rank in the method AHP	u_i	Rank in the method ANP	WJ	Rank in the method Shannon Entropy	Q	Rank in the method AHP	Q	Rank in the method ANP	WJ	Rank in the method Shannon Entropy
Imam Zadeh Davood	0.74	First	0.97	first	0.98	first	100	first	99.72	second	0.61	first	0.59	fifth	0.47	fifth	0.26	second
Keshar	0.34	Sixth	0.40	sixth	0.38	eighth	93.35	fifth	81.06	ninth	0.46	ninth	0.77	seventh	0.78	sixth	0.59	sixth
Talun	0.50	Second	0.51	second	0.69	second	95.90	second	100	first	0.57	second	0.14	second	0.17	second	0.01	first
Rendan	0.26	Eight	0.38	seventh	0.53	third	82.47	seventh	80.19	tenth	0.46	tenth	0.92	ninth	0.82	seventh	0.39	fourth
Kiga	0.19	Tenth	0.20	tenth	0.40	seventh	87.92	sixth	91.35	fifth	0.51	sixth	0.83	eighth	0.83	eighth	0.72	ninth
Sangan	0.41	Third	0.42	fifth	0.51	fourth	94.85	fourth	88.93	seventh	0.51	seventh	0.21	third	0.09	first	0.27	third
Sulqan	0.38	Fourth	0.42	fourth	0.45	sixth	95.87	third	90.86	sixth	0.52	fifth	0.47	fourth	0.43	fourth	0.46	fifth
Middle Kan	0.29	Seventh	0.30	eighth	0.50	fifth	72.78	ninth	92.03	fourth	0.53	fourth	0.96	tenth	0.89	ninth	0.67	seventh
Doab	0.38	Fifth	0.48	third	0.28	tenth	74.69	eighth	97.69	third	0.55	third	0.10	first	0.26	third	0.84	tenth
Herias	0.24	Ninth	0.22	ninth	0.37	ninth	67.91	tenth	84.07	eighth	0.48	eighth	0.72	sixth	0.92	tenth	0.71	eighth

4.3. Flooding potential of sub-watersheds using analysis of morphometric parameter

The selection of morphometric parameters in this study was predicated on their fundamental role in governing the hydrological response and flood potential of the Kan watershed. The slope is also one of the parameters that has a direct relationship with floods potential. A higher slope leads to swift runoff and an elevated rate of erosion, reducing the potential for groundwater recharge (Rai et al., 2017). The Talun and Imam-Zadeh Davood watersheds, situated on slopes between 40-60%, are considered flood-prone areas. Concerning land use, vulnerable sub-watersheds are commonly found in residential areas with low-density rangelands as land cover. These vulnerable areas mainly consist of shale with sandstone, silt stone tuff, gabbro, and diorite, and the permeability of these formations is very low, causing runoff in the watershed. One of the parameters analyzed is drainage density. The high number of streams in the watershed is attributed to its high drainage density, indicating the intensity of erosion and wastewater in different regions, influenced by the watershed's climate and lithology. The watersheds with high stream density are characterized by rapid floods that occur shortly after rainfall. The ruggedness number is indicative of the hydrological and topographic characteristics of the area and has a direct correlation with flood occurrences (Amiri et al., 2018). The circulatory ratio is influenced by the lithology of the watershed, the frequency of streams, and the gradients of different orders. A low circularity ratio suggests a low hazard of flooding, whereas a high value indicates an elevated runoff potential and, consequently, an increased risk of sudden flooding (Malik et al., 2019) . A greater length of overland flow indicates a slower runoff process, while a shorter length suggests a faster runoff process (Horton, 1945). The outflow of excess water from the watershed is dictated by the shape of the watershed, determined by the geological composition, slope, and ground cover of the area (Strahler, 1992) . The bifurcation ratio is a critical factor in watershed hydrographs, and it has an inverse relationship with watershed infiltration. Elevated bifurcation ratios suggest restricted infiltration, leading to heightened erosion and depletion of the natural resources in the watershed The elongation ratio, ranging from one for circular watersheds to 0 for elongated watersheds, helps understand the hydrological characteristics of the drainage watershed. Higher values indicate a circular shape of the watershed, associated with a substantial peak discharge and significant flood potential (Singh & Singh, 1997). The infiltration number is determined by the values of Dd and Fs, serving as a crucial parameter for assessing the watershed's infiltration potential. A higher Infiltration number corresponds to lower infiltration and increased runoff (Bhatt & Ahmed, 2014). In the Upper Kan watershed, the Talun and Imam-Zadeh Davood watersheds, with the highest infiltration number (If), signify a low infiltration capacity, leading to increased water flow in a short duration. The time of concentration is significant parameter used to calculate the potential for peak discharge in a watershed. It exhibits an inverse relationship, where larger values of Tc indicate a lower probability of sudden peak flows (Alam et al., 2021)· Stream length is an important surface runoff characteristic; a greater Lu implies reduced infiltration and an increased ability to generate runoff in a drainage network (Strahler, 1952) .

The distribution of management focus in the Kan watershed is largely influenced by geological accessibility; for instance, the Sulqan and Keshar sub-watersheds have received more attention due to their lower rocky content and ease of access, whereas the Rendan sub-watersheds remain comparatively neglected due to their predominantly rocky terrain. Geomorphologically, the majority of flood-prone areas are concentrated in the northern reaches of the watershed, characterized by high elevation and steep slopes. As noted by Mahdavi 2002, average elevation significantly influences rainfall patterns, evapotranspiration, and land cover, which in turn dictates the runoff coefficient. Our findings corroborate this, demonstrating that sub-watersheds with higher elevations and steeper gradients exhibit significantly higher flood potential.

These results align with the prioritization conducted by Gholami et al. (2020) in the Kan watershed using the HEC-RAS model. Their study indicated that increased upstream discharge elevates water levels and expands floodplain surfaces. Similarly, our findings show that while upstream sub-watersheds with sharper relief produce more constrained but intense flood zones, downstream areas experience wider inundation extents due to lower channel confinement and higher lateral expansion potential. This convergence reinforces the robustness of the hydrological and geomorphological controls identified in both studies. Regarding the methodological framework, the application of Spearman and Kendall rank correlations enhanced the reliability of the relationships between morphometric parameters and flood potential, thereby strengthening the multi-criteria evaluation. Among the tested ranking methods, the TOPSIS approach proved most effective, consistent with various studies highlighting its suitability for hydrological prioritization. However, a discrepancy was noted when compared to Kumar & Sarkar (2022), who found the AHP technique to be superior for prioritizing the Bamni Banjar sub-watersheds. This divergence can be attributed to two primary factors: (i) our study employed an objective weighting scheme (utilizing ANP and Shannon Entropy), which minimizes the subjective bias inherent in classical AHP, and (ii) the specific combination of morphometric and hydro-climatic parameters used in each study. This suggests that the performance of ranking methods is context-dependent, heavily influenced by the chosen weighting scheme and parameter set.

Furthermore, our identification of flood-prone sub-watersheds at elevations ranging from 250 to 2000 m is consistent with Ghasemlounia et al. (2021). In the Aras River basin, they emphasized that linear, areal, and relief morphometric properties collectively govern flood susceptibility. In the present study, parameters such as drainage density, stream frequency, surface runoff, initial stream order, and texture ratio also showed elevated values in high-risk areas. This convergence indicates that morphometric indices derived from Digital Elevation Models (DEMs) serve as reliable proxies for identifying critical flood-generating areas, particularly in regions where hydrometric data are limited. Finally, our findings corroborate the work of Meshram et al. (2020), Obeidat et al. (2021), and Gopinath et al. (2016), confirming that the integration of GIS-based morphometric analysis and MCDM techniques provides a practical, reproducible, and highly effective framework for watershed management and flood risk assessment. Notably, the flood hazard zones identified in this study were further validated against the HEC-HMS model results provided by the Natural Resources Organization (Table 4), which utilized the continuity equation to link flow dynamics with reservoir capacities.

Table 4. Discharge and flow volume in HEC-HMS model

Sub-watershed name	Drainage surface (sq. Km)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)	Peak discharge (cubic meters per second)	Flood volume (million cubic meters)
	Return period (year)2	Recurrence interval (year) 2	Recurrence interval (year) 2	Recurrence interval (year) 5	Recurrence interval (year) 5	Recurrence interval (year) 10	Recurrence interval (year) 10	Recurrence interval (year) 25	Recurrence interval (year) 25	Recurrence interval (year) 50	Recurrence interval (year) 50	Recurrence interval (year) 100	Recurrence interval (year) 100
Sulqan	13.6	0	0	0	0	0.2	0.08	0.4	0.24	0.9	0.56	1.3	0.85
Keshar	7.8	0	0	0	0	0.1	0.08	0.3	0.24	0.6	0.56	0.8	0.85
Talun	33.7	0	0.09	0.2	0.63	0.04	1.24	1.7	1.94	3.4	3.12	4.9	4.01
Imam-Zade Davood	10.9	0.2	0.09	0.8	0.63	1.6	1.16	2.7	1.74	5.3	2.56	7.5	3.19
Sangan	14.8	0	0	0	0	0.2	0.08	0.5	0.24	1	0.56	1.4	0.85
Kiga	6.5	0	0	0	0	0.1	0.08	2.7	1.74	0.5	0.56	0.7	0.85
Rendan	5.7	0	0	0	0	0.1	0.08	0.2	0.24	0.4	0.56	0.6	0.85
Doab	5	0.1	0.09	0.4	0.63	0.7	1.16	1.2	1.74	2.1	2.56	2.9	3.19

4.4. Validation of the models

Two correlation techniques were applied to determine the best ranking method, and the correlation between the three ranking techniques is presented in Table 4.

Spearman correlation values range from 0.41 to 0.66. Higher values, such as 0.65 and 0.66, indicate a relatively strong positive correlation, while lower values, such as 0.41, suggest a weaker positive correlation. The Spearman correlation technique exhibits a strong correlation with the ANP (TOPSIS) method. Kendall correlation values range from 0.33 to 0.58. Similar to Spearman, higher values like 0.58 indicate a relatively strong positive correlation, whereas lower values, such as 0.33, suggest a weaker positive correlation. The Kendall correlation method correlates strongly with the AHP (TOPSIS) method. Consequently, the TOPSIS technique emerges as the most effective and precise ranking method. which is consistent with the findings of Teimouri & Alvandi, 2022 and Meshram et al., 2020. TOPSIS is an optimal and reliable method. Firstly, TOPSIS selects the option with the maximum distance from the worst option and the minimum distance from the best option as the optimal choice, which contributes to its superiority over other MADM methods due to its mathematical foundation. Secondly, TOPSIS offers another advantage over certain MADM methods by being compensatory. This implies that all options and criteria weights are considered in decision-making, leaving no weight unaccounted for. Additionally, a significant number of criteria can be assessed to determine the best option. This method is straightforward, efficient, and suitable for evaluating numerous options and criteria. In general, Spearman and Kendall correlation values appear to follow similar trends, both indicating positive correlations with varying strength across different datasets. These correlation values imply a positive relationship between the measured variables, with stronger correlation values indicating closer variable alignment. The bar chart compares Spearman and Kendall Correlation Coefficients (Fig 6).

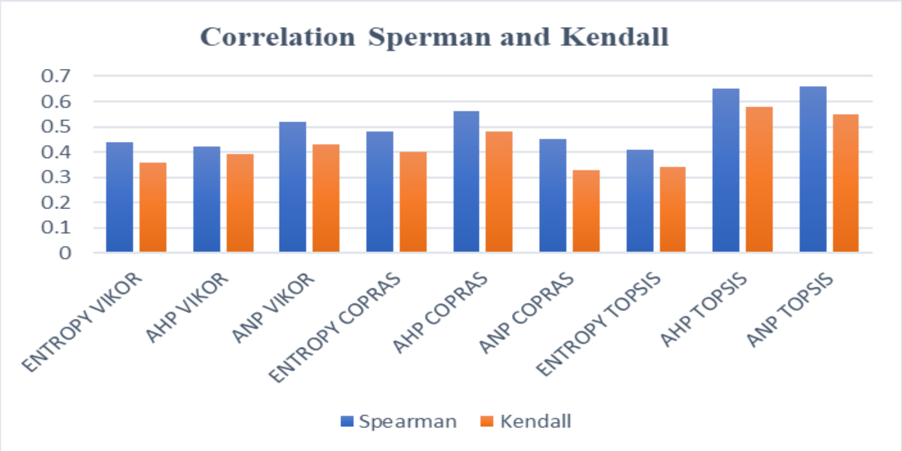

Fig. 6. Bar chart of comparing between Spearman and Kendall Correlation Coefficients

Table 5. Spearman and Kendall Correlation Coefficient for ranking method

Correlation	ENTORPY VIKOR	AHP VIKOR	ANP VIKOR	ENTORPY COPRAS	AHP COPRAS	ANP COPRAS	ENTROPY TOPSIS	AHP TOPSIS	ANP TOPSIS
Spearman	0.44	0.42	0.52	0.48	0.56	0.45	0.41	0.65	0.66
Kendall	0.36	0.39	0.43	0.40	0.48	0.33	0.34	0.58	0.55

5. Conclusions

This study prioritized flood-prone sub-watersheds in the Kan watershed by comparing multiple decision-making methods. Among the evaluated techniques, TOPSIS demonstrated the highest accuracy in ranking, showing strong correlation with Spearman and Kendall coefficients. The findings consistently identified Imam-Zadeh Davood and Talun as the most critical sub-watersheds, driven by high values in morphometric (circularity ratio, drainage density), topographic (slope, ruggedness), and climatic (rainfall intensity) parameters. These results were further validated by the HEC-HMS model, which aligned with the ANP and Shannon Entropy approaches.

To mitigate flood risks, immediate management interventions are required in the identified high-risk areas. Specifically, implementing nature-based solutions (NBS) such as reforestation and sediment control in high-slope sub-watersheds is recommended to reduce runoff velocity. Furthermore, strict enforcement of buffer zone regulations along riverbanks is essential to prevent unauthorized construction and preserve natural riverbed functions. Future research should transition from static assessment to dynamic modeling by integrating machine learning algorithms and real-time remote sensing data (e.g., soil moisture and river levels). Expanding the criteria to include socio-economic impacts will also provide a more holistic framework for integrated water resources management in the Kan watershed.

Table 6. Table of Abbreviations

The full name of the term	Abbreviations
Analytical Hierarchy process	AHP
Analytical Network Process	ANP
Technique for Order Preference by Similarity to Ideal Solution	TOPSIS
Vlse Kriterijumsk Optimizacija Kompromisno Resenje	VIKOR
Complex Proportional Assessment	COPRAS
Multiple-Criteria Decision Analysis	MCDA
Geography Information system	GIS
Spearman Correlation Coefficient Test	SCCT
Kendall Tau Correlation Coefficient Test	KTCCT
Digital Elevation Model	DEM
Hydrologic Engineering Center - Hydrologic Modeling System	HEC_HMS

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References

Adnan, S. G., & Kreibich, H. (2016). An evaluation of disaster risk reduction (DRR) approaches for coastal delta cities: a comparative analysis. Natural Hazards, 83, 1257–1278.

Aher, P. D., Adinarayana, J., & Gorantiwar, S. D. (2014). Quantification of morphometric characterization and prioritization for management planning in semi-arid tropics of India: a remote sensing and GIS approach. Journal of Hydrology, 511, 850–860.

Ahmadisharaf, E., Kalyanapu, A. J., & Chung, E.-S. (2015). Evaluating the effects of inundation duration and velocity on selection of flood management alternatives using multi-criteria decision making. Water Resources Management, 29, 2543–2561.

Alam, A., Ahmed, B., & Sammonds, P. (2021). Flash flood susceptibility assessment using the parameters of drainage basin morphometry in SE Bangladesh. Quaternary International, 575, 295–307.

Alizadeh, A. (2010). Principles of applied hydrology. 30, 5. University of Emam Reza, Mashhad, Iran, 991, 2010–2011.

Amiri, M., Pourghasemi, H., & Arabameri, A. (2018). Prioritization of flood inundation sub-watersheds of Maharlo watershed in Fars province using morphometric parameters and VIKOR decision making model. Iranian Journal of Ecohydrology, 5(3), 813–827.

Amiri, M., Pourghasemi, H. R., Arabameri, A., Vazirzadeh, A., Yousefi, H., & Kafaei, S. (2019). Prioritization of flood inundation of Maharloo Watershed in iran using morphometric parameters analysis and TOPSIS MCDM model. In Spatial modeling in GIS and R for earth and environmental sciences (pp. 371–390). Elsevier.

Azizian, A., & Shokoohi, A. (2015). Effects of data resolution and stream delineation threshold area on the results of a kinematic wave based GIUH model. Water SA, 41(1), 61–70.

Bhatt, S., & Ahmed, S. A. (2014). Morphometric analysis to determine floods in the Upper Krishna basin using Cartosat DEM. Geocarto International, 29(8), 878–894.

Chung EunSung, C. E., Won KwangJae, W. K., Kim YeonJoo, K. Y., & Lee HoSun, L. H. (2014).

Dehghanian, N., Saeid Mousavi Nadoushani, S., Saghafian, B., & Damavandi, M. R. (2020). Evaluation of coupled ANN-GA model to prioritize flood source areas in ungauged watersheds. Hydrology Research, 51(3), 423–442.

Dovonce, E. (2000). A physically based distributed hydrologic model. Master of Science Thesis, the Pennsylvania State University.

Fairfield, J., & Leymarie, P. (1991). Drainage networks from grid digital elevation models. Water Resources Research, 27(5), 709–717.

Falah, F., Rahmati, O., Rostami, M., Ahmadisharaf, E., Daliakopoulos, I. N., & Pourghasemi, H. R. (2019). Artificial neural networks for flood susceptibility mapping in data-scarce urban areas. In Spatial modeling in GIS and R for Earth and Environmental Sciences (pp. 323–336). Elsevier.

Faniran, A. (1968). The index of drainage intensity: a provisional new drainage factor. Aust J Sci, 31(9), 326–330.

Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press.

Ghadimi.M, B. . (2013). the effective soil factors in the distribution of vegetative types on Mighan playa Iran variables. Journal of Agricultural Science, 3(5), 199–204.

Ghadimi, M., Hajihasani, N., Malekian, A., & Moghimi, E. (2022). Flood potential assessment of the Kan basin using morphometric pharameters. Journal of Range and Watershed Managment, 75(4), 539–551. https://doi.org/10.22059/jrwm.2021.311132.1537

Ghadimi, M., keynezhad, A., & Narouei, R. (2024). The effect of karstification on water resource hazards management based on physicochemical factors of water (case study: Valiabad – Hezarcham), Iran. Environmental Management Hazards, 10(4), 335–354. https://doi.org/10.22059/jhsci.2024.373119.819

Ghasemlounia, R., & Utlu, M. (2021). Flood prioritization of basins based on geomorphometric properties using principal component analysis, morphometric analysis and Redvan's priority methods: A case study of Harşit River basin. Journal of Hydrology, 603, 127061.

Gholami, M., Ganavati, E., & Ahmadabadi, A. (2020). Simulation of floodplain zones in Tehran's metropolitan watershed (case study: Kaan basin). Journal of Spatial Analysis Environmental Hazarts, 6(4), 95–108.

Gopinath, G., Nair, A. G., Ambili, G. K., & Swetha, T. V. (2016). Watershed prioritization based on morphometric analysis coupled with multi criteria decision making. Arabian Journal of Geosciences, 9, 1–17.

Guo, E., Zhang, J., Ren, X., Zhang, Q., & Sun, Z. (2014). Integrated risk assessment of flood disaster based on improved set pair analysis and the variable fuzzy set theory in central Liaoning Province, China. Natural Hazards, 74, 947–965.

Horton, R. E. (1932). Drainage-basin characteristics. Transactions, American Geophysical Union, 13(1), 350–361.

Horton, R. E. (1945). Erosional development of streams and their drainage basins; hydrophysical approach to quantitative morphology. Geological Society of America Bulletin, 56(3), 275–370.

Hwang, C.-L., Yoon, K., Hwang, C.-L., & Yoon, K. (1981). Methods for multiple attribute decision making. Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey, 58–191.

Kirpich, Z. P. (1940). Time of concentration of small agricultural watersheds. Civil Engineering, 10(6), 362.

Kumar, P., & Sarkar, P. (2022). A comparison of the AHP and TOPSIS multi-criteria decision-making tools for prioritizing sub-watersheds using morphometric parameters' analysis. Modeling Earth Systems and Environment, 8(3), 3973–3983.

Mahammad, S., Mofizul Hoque, M., & Islam, A. (2022). Morphometry-based subwatershed prioritization for flood potentiality analysis of the gumani river basin (India) using TOPSIS. Drainage Basin Dynamics: An Introduction to Morphology, Landscape and Modelling, 417–440.

Mahdavi, M. (2002). Applied hydrology. Tehran University Press, 2, 437.

Mahmoodi, E., Azari, M., & Dastorani, M. T. (2023). Comparison of different objective weighting methods in a multi-criteria model for watershed prioritization for flood risk assessment using morphometric analysis. Journal of Flood Risk Management, 16(2), e12894.

Malekian, A., & Azarnivand, A. (2016). Application of integrated Shannon's entropy and VIKOR techniques in prioritization of flood risk in the Shemshak watershed, Iran. Water Resources Management, 30, 409–425.

Malik, A., Kumar, A., & Kandpal, H. (2019). Morphometric analysis and prioritization of sub-watersheds in a hilly watershed using weighted sum approach. Arabian Journal of Geosciences, 12, 1–12.

Melton, M. A. (1957). An analysis of the relations among elements of climate, surface properties, and geomorphology (Vol. 11). Department of Geology, Columbia University New York.

Meshram, S. G., Alvandi, E., Meshram, C., Kahya, E., & Fadhil Al-Quraishi, A. M. (2020). Application of SAW and TOPSIS in prioritizing watersheds. Water Resources Management, 34, 715–732.

Miller, V. C. (1953). Quantitative geomorphic study of drainage basin characteristics in the Clinch Mountain area, Virginia and Tennessee. Technical Report (Columbia University. Department of Geology); No. 3.

Moghimi, E., Glade, T., Al-Ansari, N., & Shahabi, H. (2025). Floods and New Housing Design Theory to Sustain and Reduce Hazards (A Scientific Strategy). Geofluids, 2025, 1416016. https://doi.org/10.1155/gfl/1416016

Moore, I. D., Grayson, R. B., & Ladson, A. R. (1991). Digital terrain modelling: a review of hydrological, geomorphological, and biological applications. Hydrological Processes, 5(1), 3–30.

Mukherjee, F., & Singh, D. (2020). Detecting flood prone areas in Harris County: A GIS based analysis. GeoJournal, 85(3), 647–663.

Obeidat, M., Awawdeh, M., & Al-Hantouli, F. (2021). Morphometric analysis and prioritisation of watersheds for flood risk management in Wadi Easal Basin (WEB), Jordan, using geospatial technologies. Journal of Flood Risk Management, 14(2), e12711.

Opricovic, S., & Tzeng, G.-H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455.

Rahman, M. S., Di, L., Yu, E., Lin, L., Zhang, C., & Tang, J. (2019). Rapid flood progress monitoring in cropland with NASA SMAP. Remote Sensing, 11(2), 191.

Rai, P. K., Mohan, K., Mishra, S., Ahmad, A., & Mishra, V. N. (2017). A GIS-based approach in drainage morphometric analysis of Kanhar River Basin, India. Applied Water Science, 7, 217–232.

Rehman, S. U., Ahmed, A., Gilja, G., Valyrakis, M., Ghumman, A. R., Pasha, G. A., & Farooq, R. (2024). A Laboratory Study of the Role of Nature-Based Solutions in Improving Flash Flooding Resilience in Hilly Terrains. In Water (Vol. 16, Issue 1). https://doi.org/10.3390/w16010124

Roy, D. C., & Blaschke, T. (2015). Spatial vulnerability assessment of floods in the coastal regions of Bangladesh. Geomatics, Natural Hazards and Risk, 6(1), 21–44.

Saaty, T. L. (1986). Axiomatic foundation of the analytic hierarchy process. Management Science, 32(7), 841–855.

Saaty, T. L. (2005). Theory and applications of the analytic network process: decision making with benefits, opportunities, costs, and risks. RWS publications.

Schumm, S. A. (1956). Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey. Geological Society of America Bulletin, 67(5), 597–646.

Shakoor, A., Ghumman, A. R., Arif, M., Pasha, G. A., & Masood, A. (2024). GIS-Based Assessment of Flash Flood Susceptibility around Thuwal-Rabigh Region, Saudi Arabia.

Shannon, C. E. (1948). A mathematical theory of communication. The Bell System Technical Journal, 27(3), 379–423.

Singh, N., Jha, M., Tignath, S., & Singh, B. N. (2020). Morphometric analysis of a badland affected portion of the Mandakini River sub-watershed, central India. Arabian Journal of Geosciences, 13, 1–14.
Singh, S., & Singh, M. C. (1997). Morphometric analysis of Kanhar river basin. National Geographical Journal of India, 43(1), 31–43.
Strahler, A. N. (1952). Hypsometric (area-altitude) analysis of erosional topography. Geological Society of America Bulletin, 63(11), 1117–1142.
Strahler, A. N. (1992). Quantitative/dynamic geomorphology at Columbia 1945-60: a retrospective. Progress in Physical Geography, 16, 65–84. https://doi.org/10.1177/030913339201600102
Teimouri, M., & et al. (2022). Comparison of Models TOPSIS, SAW, ELECTRE and VIKOR in order to the prioritization of sedimentation and flood hazard of watersheds. Journal of Environmental Science and Technology, 1, 79–99. https://doi.org/10.30495/jest.2022.45404.4731
Yang, X., Ding, J., & Hou, H. (2013). Application of a triangular fuzzy AHP approach for flood risk evaluation and response measures analysis. Natural Hazards, 68, 657–674.
Zavadskas, E. K., Kaklauskas, A., & Šarka, V. (1994). The new method of multicriteria complex proportional assessment of projects.